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Diabetic Retinopathy Detection Based on Eigenvalues of the Hessian Matrix

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Abstract

Diabetic Retinopathy (DR) is a medical condition caused by fluctuating insulin level in the blood which causes vision loss in case of severity. Timely treatment of such risks requires identification of the first clinical symptoms like microaneurysms (MAs) and hemorrhages (HMAs). The presence of those symptoms are visible in the digital color photographs of the retina and appear as round dark red spots in the image. In this paper, two approaches in the detection of MAs and HMAs are proposed. First, the semi automated approach applies semi automated hessian-based candidate selection algorithm (SHCS) followed by thresholding to detect true MAs and HMAs. The automated approach applies automated hessian-based candidate selection algorithm (AHCS) followed by feature extraction and SVM classification that uses twenty images for training manually annotated by medical domain experts. Implementations of both the approaches have been tested on real world images from retinal scan. From the results, the detection rate of automated algorithm when compared with that of the semi automated algorithm has been found to be significantly lesser with a probability $p<0.005$.

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Keywords: Diabetic retinopathy;Microaneurysms;Hemorrhages;SVM ;SHCS;AHCS;

1. Introduction

Diabetic Retinopathy (DR) is a retinal disorder which is the common cause of vision loss in many of the

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diabetic patients. The World Health Organization estimates that 135 million people have diabetes mellitus worldwide and that the number of people with diabetes will increase to 300 million by the year 2025 [1]. The problem is further complicated by the fact that DR does not exhibit any distinctive symptoms which the patient can easily perceive until a severe stage is reached. Therefore, regular eye check-up and timely treatment is needed [2]. However, the lack of specialized ophthalmologists together with associated higher medical costs makes regular check up costly [2]. To fill this gap, development of low cost and versatile Computer Aided Diagnosis (CAD) systems can be used in clinical environments and have drawn much more attention in recent years [2].

Hemorrhages and Microaneurysms are the foremost clinical signs that indicate the presence of diabetic retinopathy. These signs fall into a single category referred to as red lesions. Microaneurysms are minute blood-filled bulges in the artery walls as shown in Fig.1. Hemorrhages damage the retensitive tissue of the back wall of the eye and appear as red spots slightly larger than microaneurysms as shown in Fig.1. Niemijer et al. proposed an MA detection method based on morphological top-hat transform followed by pixel classification using k-nearest neighbor algorithm [3]. Sanchez et al. proposed a logistic regression based detection method [4]. Cree et al. proposed a top-hat transform based detection method followed by Bayes classification [5].

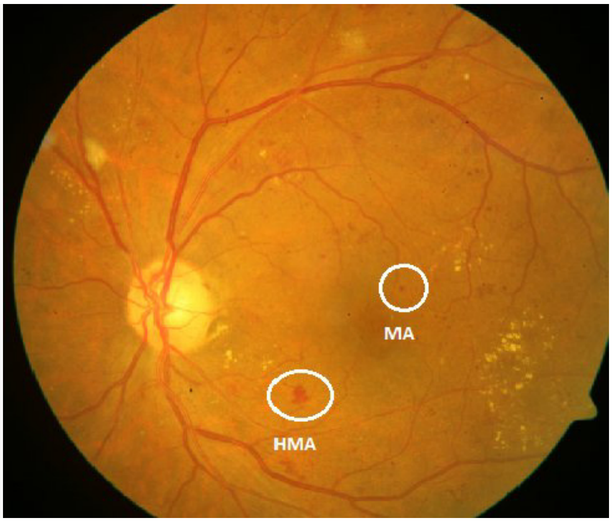


Fig.1. Retinal image showing Microaneurysms and hemorrhages

Quellec et al. proposed a method wavelet transform based template matching for MA detection [6]. Zhang et al. proposed a method based on a multiscale Gaussian correlation and space representation classifier [7, 8]. Antal et al. proposed a detection method based on ensemble learning [9, 10]. Lazar et al. proposed a detection method based on cross sectional profile analysis [11]. Fegyver et al. proposed a method based on concentration gradient analysis [12]. Giancardo et al. proposed a detection method based on the Radon transform [13]. This paper focuses on identifying MAs and HMAs based on the analysis of eigenvalues of the image Hessian matrix. The advantage of this approach is that basing on the eigenvalues not only detects vessel-like, but also sheet-like or blob-like structures [14, 15].

This paper is organized as follows: Section 2 presents the overview of both automated and semi automated approach towards DR detection. Section 3 presents semi automated approach explained in detail. In Section 4 automated Hessian based DR detection is covered. In Section 5 testing and results of implementation of both the methods is presented. The paper ends with a short summary in Section 6.

2. Diabetic Retinopathy Detection

Microaneurysm and Hemorrhage candidate selection is the critical part in detection of diabetic retinopathy. Microaneurysms and hemorrhages appear as dark spots in the retinal fundus images. In this paper, two approaches in the detection of MAs and HMAs have been proposed. First, the semi automated approach applies SHCS algorithm followed by thresholding to detect true MAs and HMAs. The automated approach applies AHCS algorithm followed by feature extraction and classification using SVM.

3. Semi Automated DR Detection Using Eigen Value Analysis

In the semi automated approach image processing techniques are applied to reduce noise and other disturbances captured during image acquisition which may lead to false detection of the disease. Then, SHCS algorithm based on Hessian matrix is applied to extract image regions which are more likely to be MAs. Then thresholding applied removes false positives and detects true MAs and HMAs.

3.1 Analysis of Eigenvalues of the Hessian Matrix

Microaneurysm and Hemorrhages are extracted using the eigen values of the hessian matrix. For each image point, the second order partial derivatives are computed (1). Such matrix of second order derivatives forms the so-called hessian matrix. The partial derivatives are calculated as voxel intensity differences in the neighbourhood of the voxel [16]. The Hessian matrix describes the 2nd order local image intensity variations around the selected voxel [17].

$$\begin{aligned} H(x,y) &= \begin{bmatrix} L_{xx}(x,y) & L_{xy}(x,y) \\ L_{yx}(x,y) & L_{yy}(x,y) \end{bmatrix} \\ L_{xx}(x,y) &= G_{xx}(x,y) * I(x,y) \\ L_{xy}(x,y) &= G_{xy}(x,y) * I(x,y) \\ L_{yx}(x,y) &= G_{yx}(x,y) * I(x,y) \\ L_{yy}(x,y) &= G_{yy}(x,y) * I(x,y) \end{aligned} \tag{1}$$

where * is the convolution operator, I(x,y) is the preprocessed image, and $G_{xx}(x,y)$, $G_{xy}(x,y)$, $G_{yx}(x,y)$ and $G_{yy}(x,y)$ are second order partial derivative functions of the Gaussian function G(x,y) in each direction. The Gaussian function is given in equation 2.

$$G(x,y) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \tag{2}$$

The green channel of the fundus image given as input to the Hessian operator extracts circular-dark regions that exhibit strong derivatives in two orthogonal directions. From the obtained Hessian matrix its eigenvalues are calculated. With the known eigen values, the model it belongs to and the resulting theoretical behavior of the eigenvalues, the voxel can be analyzed to check if it belongs to the structure being searched [14]. The final regions are selected by applying thresholding to the eigen values λ1 and λ2.Table 1 summarizes the relations between λi and the orientation of a structure in the image.

Table 1: Eigenvalues of the Hessian matrix and image structure orientation (L low, H+ high positive, H- high negative)

λ1	**λ2**	**Structure orientation**
L	L	Noise
L	L	Bright sheet-like-structure
L	L	Dark sheet-like-structure
L	H-	bright tubular structure
L	H+	dark tubular structure
H-	H-	bright blob-like structure
H+	H+	dark blob-like structure

3.2 Semi Automated DR Detection

The flow diagram of the semi automated DR detection scheme is shown in Fig. 2. RGB color image given as input is converted to inverted green-channeled image as the contrast of the symptoms appear to be high in green channel. Upon extracting the green channel of the image, a low-pass filter based on Fast Fourier Transform (FFT) is applied to lower in degree the noise in the image. MA candidate regions are obtained by using eigenvalue analysis based on a Hessian matrix. The candidates are therefore classified into red lesions by applying thresholding technique.

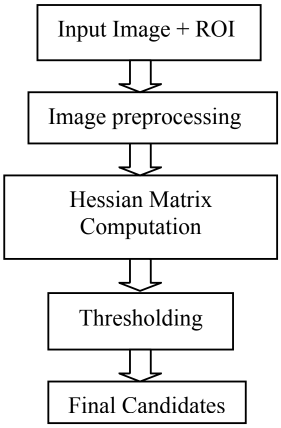


Fig.2. Work Flow Diagram of Semi Automated DR Detector

The semi automated algorithm presented in Algorithm 1 starts by applying the preprocessing techniques. Then for each of the image pixels Hessian matrix is formed and the eigenvalues λ1, λ2 are computed. Thresholding applied on the resulting eigen values identifies the true MAs and HMAs.

Given an image I:

Apply Pre-processing techniques.

Compute the Hessian Matrix, H at $\sigma = 1, 2, 3$

Compute $\lambda 1$ and $\lambda 2$ of H

$I_{final} = (\lambda 1 < \text{Threshold1}) \cap (\lambda 2 < \text{Threshold2})$

Algorithm 1: Semi automated hessian-based candidate selection algorithm (SHCS)

Two empirically chosen threshold values Threshold1 = -2 and Threshold2 = -1 have been used. The thresholding operation applied eliminates the false positives from the candidate regions and results in true MAs and HMAs detection.

4. Automated DR Detection Using Eigen Value Analysis

Automated DR detection scheme starts by applying image Pre-processing techniques followed by maximum region extraction. Then possible candidate regions are obtained by using eigenvalue analysis based on a Hessian matrix as mentioned in section 3.1. To the resulting image, feature analysis is performed and the final candidates are obtained using SVM classifier which classifies the possible candidates to final MAs and HMAs. The flow diagram of the Automated DR detection scheme is shown in Fig. 3.

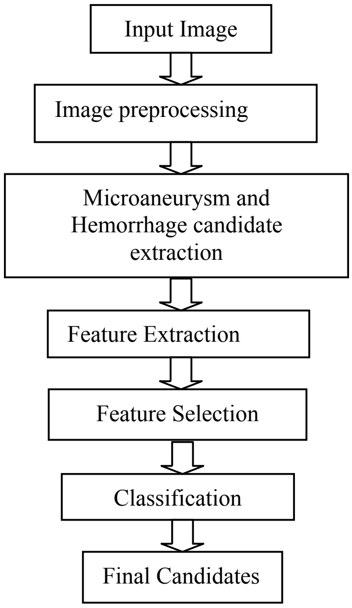


Fig.3. Work Flow Diagram of Automated DR Detector

Then maximum region is extracted which is the connected component of pixels with a given constant intensity value. Pixels of the image are processed row wise and compared to their 8 nearest neighbours. Pixel is recognized as a maximum region if all neighbours have intensity at a lower or same degree. For each selected candidate region within the fundus images feature extraction is done by dividing each interest point region into 9X9 sub-windows and computing the GLCM features within each sub-window. In total, 16 basic features are selected by sorting those features based on their weighted values.

Given an image I:

- Apply Pre-processing techniques.
- Create image $I_{connect}$ with connected components identified
- Compute the Hessian Matrix, H and λ1 , λ2 at $\sigma = 1, 2, 3$
- Create candidate image I_{cand}:

  $I_{cand} = (\lambda 1 < \text{Threshold1}) \cap (\lambda 2 < \text{Threshold2})$

  Two empirically chosen threshold values Threshold1 = -2 and Threshold2 = -1 have been used.

  Merge $I_{connect}$ and I_{cand}

Algorithm 2: Automated Hessian Based MAs and HMAs candidate selection (AHCS)

SVM classifier is trained using ten fundus images which are manually annotated by ophthalmologist. In training, positive and negative samples are taken from the annotations of training images. Then Principal Component Analysis (PCA) is applied to train the classifier. In the final classification phase, SVM classifier applied detects true MAs and HMAs.

5. Experimental Results And Analysis

In this paper a semi automated approach and an automated approach have been proposed for DR detection. The semi automated approach applies SHCS algorithm followed by thresholding to detect true MAs and HMAs. The automated approach applies AHCS algorithm followed by feature extraction and SVM classification for DR detection. The SVM classifier has been trained with 20 images manually annotated by medical experts from Lotus Eye Care Hospital, Coimbatore. Both the methods have been implemented in MATLAB and tested on ten real world images from retinal scan as shown in Fig.4. The results of semi automated and automated approach can be seen in

Fig.5 and Fig.6 respectively. The performances of the proposed methods are evaluated based on True positive Rate (TPR) and the number of false positives per image (FPI). TPR is defined to be the number of correct positive results obtained during the test from all the positive samples used. FPI is defined to be the number of incorrect positive results obtained during the test.

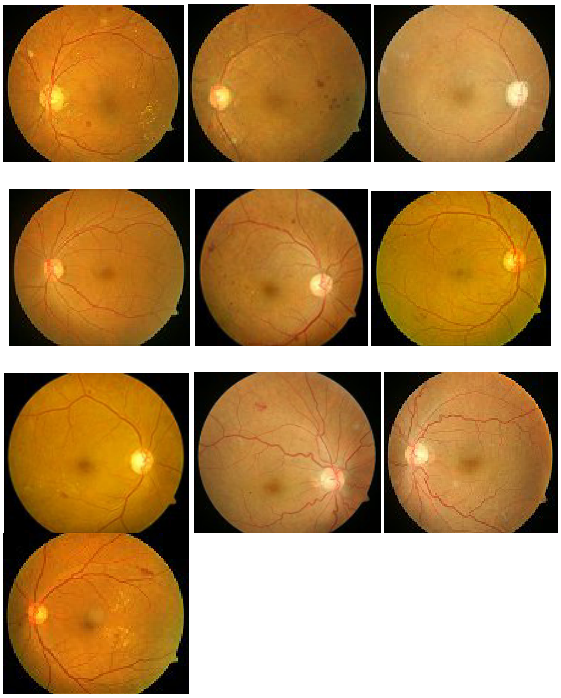
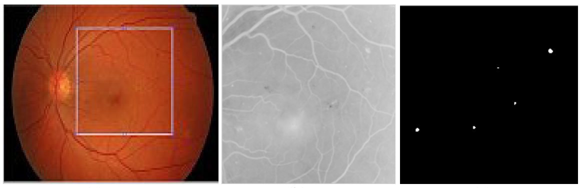
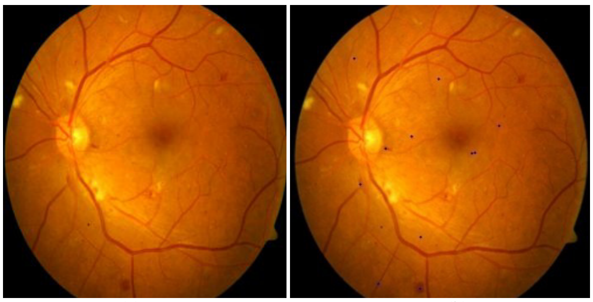


Fig 4. Retinal Images used for testing



(a) (b) (c)

Fig.5. Semi automated detection results (a) Original image with ROI selected (b) green channel of the selected region (c) MA and HMA detection results



(a) (b)

Fig.6. Automated detection results (a) Original Image (b) MA and HMA detection image

From the observations made, the detection rates of both the automated and the semi automated approach are calculated and listed in Table 2.

Table 2. Automated and semi automated red lesion detection rate.

Method	TPR MA	TPR HMA	TPR Red Lesion	FPI
Automated	39.53	50	45.36	43.29
Semi Automated	79.06	87.03	83.05	26.80

The Fig.7 gives the comparison of the DR detection rates of both the automated and the semi automated approaches.

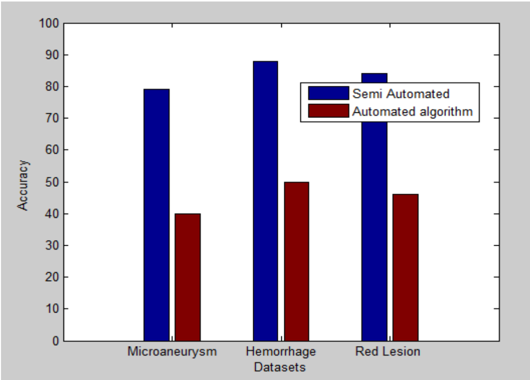


Fig.7. Detection rate comparison of automated and semi automated MAs and HMAs systems

In Fig.7 the vertical blue bar indicates the result of semi automated approach and the vertical red bar indicates the result of automated approach. From the results shown diagrammatically in Fig.7 it can be inferred that the detection rate of automated approach is lesser than that of semi automated approach with probability $p < 0.005$.

6. Conclusion and Future Work

In this paper, Semi automated hessian-based candidate selection algorithm (SHCS) and Automated hessian-based candidate selection algorithm (AHCS) have been developed and tested on real world retinal images. From the result the detection rate of automated algorithm when compared with that of the semi automated algorithm has been found to be significantly lesser with a probability $p < 0.005$. The results are validated by medical domain experts and it has been concluded that the semi automated algorithm is valid from clinician's point of view and it still requires further improvement for the early detection of the disease. The semi automated method can be further improved by removing the false positives appearing in the optic disc region, tight vessel curving and vessel crossings of the retinal image. However, obtained results of automated method show that the method is able to perform the DR detection, but it requires further development and parameter tuning to be fully adapted to this specific purpose.

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